Research Institute for Environmental Economics and Management

Discussion Paper Series No.2101

Success and Failure of the Voluntary Action Plan: Disaggregated Sector Decomposition Analysis of Energy-related CO2 Emissions in Japan

Guanyu Lu, Makoto Sugino, Toshi H Arimura & Tetsuya Horie

May 2021

WASEDA

Abstract

To accomplish the goal of greenhouse gas (GHG) emissions reduction, the Japanese Business Federation (JBF) has implemented the voluntary action plan (VAP), a unique feature of which does not penalize industrial firms or organizations, even if they fail to meet the CO_2 emissions or energy consumption reduction goals. This study evaluates the role of VAP in emission reduction by analyzing highly disaggregated data from 1980 to 2015 of approximately 400 sectors using the logarithmic mean Divisia index (LMDI) method. The results indicate that the increase in CO_2 emissions among Japanese industries is mainly caused by the increase in indirect CO_2 emissions. Moreover, the energy consumption structure has progressively shifted from fossil fuels to electricity. The decomposition analysis highlights two key points. (1) The VAP is ineffective in reducing emissions in sectors with low market concentration. (2) The energy intensity target of the VAP does not lead to a significant reduction in CO_2 emissions. Thus, this study concludes that the contribution of the VAP in reducing CO_2 emissions is limited. Evidence from our research suggests three directions for future policy design and implications.

Keywords: Voluntary action plan, Decomposition analysis, Japan

1 Introduction

To mitigate the salient impacts of climate change, Japan has actively participated in various conventions, such as the Kyoto Protocol (1997) and the Paris Agreement (2018). To meet the reduction target of the Kyoto Protocol, the Japanese government committed to reducing its greenhouse gas (GHG) emissions by 6% between 2008 and 2012 compared to the 1990 level (UNFCCC, 1997).

In the political context, to avoid governmental intervention in the form of environmental regulations, the Japanese Business Federation (hereafter referred to as JBF) implemented the voluntary action plan (VAP) to reduce GHG emissions and solid waste generation from 1997 to 2012 (Sugino and Arimura, 2011; Sugiyama and Imura, 1999). Before 2010, unlike the European Union (EU), under the Kyoto Protocol, Japan did not implement explicit carbon policies, such as a domestic emission trading scheme (ETS) or a carbon tax, to combat climate change. In the Japanese manufacturing sector, emission reduction mainly relied on the VAP[1]. Compared with other environmental policies, the regulatory authority cannot punish firms that failed to meet the emission reduction target, when they participate in the VAP. Moreover, firms can freely choose whether or not to participate in the VAP.

---

[1] The Tokyo metropolitan government implemented an ETS in 2010. However, the service sector is the main target of this ETS (Arimura and Abe, 2021). Thus, mitigation efforts in the manufacturing sector depended on the VAP.

As Jones and Yoo (2009) argued, pressure from society, the government, and nongovernmental organizations encourages firms to comply with voluntary targets. Thus, firms' reputations may be damaged if they do not participate or fail to meet the targets set forth by the VAP, which would inflict indirect damage to these firms. In addition, the progress of the VAP was monitored by a governmental committee under the Ministry of Economy, Trade and Industry (METI). Furthermore, JFB allowed associations and industries to set the type of target by themselves, which were classified as CO_2 absolute targets, CO_2 intensity targets, energy absolute targets, and energy intensity targets (Arimura, 2015). Few studies have focused on individual firms in terms of whether they met the voluntary targets. For instance, Wakabayashi and Arimura (2016) observed that the VAP encourages small and medium-sized enterprises (SMEs) to set reduction targets. However, Arimura et al. (2019) suggested that agreements on voluntary targets can be relatively easily achieved when emissions are concentrated among few firms.

However, it is necessary to clarify whether emission reduction was achieved successfully through the implementation of the VAP or through other factors, such as changes in industrial structure, technical innovation, and economic recessions. To do so, this study quantifies the driving factors behind the changes in energy-related CO_2 emissions, which will provide us with valuable information to evaluate the effectiveness of current and future policies and thus enable us to provide options in designing regulations to realize emission reduction targets.

The majority of the literature focusing on the drivers of the changes in CO2 emissions is summarized in Table 1, which highlights the studies that have explored the factors that contribute to changes in CO2 emissions in Japan. However, most studies have focused only on the manufacturing sector or used highly aggregated data consisting of fewer than 100 sectors (for example, Liu et al., 2019; Su et al., 2017). Highly aggregated data are easy to handle but aggregate vital industries, such as energy-intensive trade-exposed industries, which is not ideal from the policy-making perspective.

<Table 1 approximately here>

Empirical evidence suggests that Japan has successfully reduced its domestic CO_2 emissions from the manufacturing industry (Nishitani et al., 2012). Most studies that have analyzed Japanese CO_2 emissions have considered only direct emissions from the manufacturing industry. For instance, Matsumoto et al. (2019) found that the energy intensity effect was the main driver of increasing CO_2 emissions in the manufacturing sector at the regional level between 1993 and 2013. However, as electricity consumption continues to increase, the indirect CO_2 emissions emitted from fossil fuel combustion have become an important part of CO_2 emissions, which cannot be ignored. Furthermore, the service industry, which has expanded in many developed countries, mostly uses electricity, rather than fossil fuel, as an energy source. Thus, the direct CO_2 emissions of this industry are relatively small. Consequently, compared with other industries, the service industry tends to emit a larger share of indirect CO_2 emissions, which indicates the importance of considering indirect emissions (Nansai et al., 2009). For example, Zhang et al. (2015) showed that the indirect CO_2 emissions from the service industry were greater than direct emissions based on a multiregional input-output model between 1995 and 2007.

In this study, we use highly disaggregated data consisting of approximately 197 integration sectors, including all industries, to explore the driving factors the changes in total Japanese CO2 emissions. Concurrently, we also attempt to bridge the gap in the literature by evaluating whether the VAP successfully reduced CO_2 emissions from the manufacturing sector in Japan.

We use the estimated CO_2 emissions provided by the "Embodied Energy and Emission Intensity Data for Japan Using Input-Output Tables" (3EID). Our results provide evidence that the VAP tends to succeed in reducing emissions in sectors with high market concentration. However, the energy intensity target of the VAP achieves limited success in reducing emissions compared to other targets. Furthermore, the increase in indirect CO_2 emissions is the main driver of the rising CO_2 emissions in Japanese industries. Moreover, the decomposition results show evidence of the expansion of the service industry during the study period. This study also exhibits the driving forces on changes in CO2 emissions for 197 sectors. It allows us to present the detailed regulation options that need to be considered when designing regulations.

The contribution of this research is fourfold. First, we investigate the effectiveness of the VAP within the manufacturing industry from 1990 to 2011 by using the decomposition method. To the best of our knowledge, only a few studies have examined the impact of Japan's VAP on CO_2 emissions. Second, compared to the existing literature, which mostly focuses on direct emissions, we consider both direct and indirect CO_2 emissions. Third, the existing literature has focused on the manufacturing sector, whereas this study examines CO_2 emissions from both the service industry and the manufacturing sector. Finally, previous studies have used highly aggregated industrial data. However, this study focuses on approximately 400 sectors representing the entire Japanese economy, which allows us to investigate in detail what happened within Japanese industries.

The remainder of the study is organized as follows. Section 2 describes the methodology and the data. Section 3 presents our analysis and discusses the driving forces of total CO_2 emissions and suggestions for the implementation of regulations at the sectoral level. Section 4 concludes the study by suggesting directions for future research.

2 Methodology and data

2.1 Methodology

The logarithmic mean Divisia index (LMDI) method has been widely used to investigate the drivers of changes in CO_2 emissions. The advantages of the LMDI method include 1) the ability to factor reversal properties without leaving residuals, 2) the handling of zero values, and 3) consistency in aggregation (Ang, 2004, 2005, 2015; Zhang et al., 2016). Moreover, both additive and multiplicative decomposition analyses are used in the LMDI method. Additive decomposition analysis exhibits the aggregation of quantity-decomposed effects with a physical unit (Ang, 2015; Wang and Feng, 2017), while multiplicative decomposition analysis exhibits the aggregation of intensity-decomposed effects without a physical unit (Su et al., 2017).

In this study, the additive LMDI method is adopted to investigate the changes in total CO_2 emissions in Japan from 1980 to 2015. To evaluate how each sector contributes to the changes in CO_2 emissions in the long term, this study follows Grossman (1995) to decompose the changes in CO_2 emissions into scale, composition, and technique effect at the most detailed sectoral level based on Japanese domestic input-output tables from 1980 to 2015. The scale effect reflects the changes in pollution emissions brought about by changes in economic activities, the composition effect represents the changes in emissions induced by changes in the industrial structure, and the technique effect reflects the changes in emissions due to changes in emission intensity.

Since the total CO_2 emissions are emitted by N sectors in an economy, each sector emits e_i. Let yi represent the output for sector i, and Y represent the total output for the entire economy. Thus, following Levinson (2009), the aggerated CO_2 emissions can be written as:

$$CO_2 = \sum_{i=1}^{N} e_i = \sum_{i=1}^{N} \frac{co_{2i}}{yi} \times \frac{yi}{Y} \times Y = Y \sum_{i=1}^{N} \varphi_i \theta_i \quad (1),$$

where θ is the share of sectorial output to total output, and φ is the CO_2 intensity for each sector. In the additive LMDI method, the changes in CO_2 emissions between period *t* and the previous period *t-1* are represented by three factors:

$$\Delta CO2 = CO2^{t} - CO2^{t0} = \sum_{i=1}^{N} e_i^{t} - \sum_{i=1}^{N} e_i^{t-1} = \Delta E_{tot} = \Delta E_Y + \Delta E_{\varphi_i} + \Delta E_{\theta_i} \quad (2),$$

where the three elements in equation (2) represent the scale (ΔE_Y), composition (ΔE_{φ_i}), and technique (ΔE_{θ_i}) effects. The LMDI method leaves no residual in the decomposition process, leading to its uniqueness. Furthermore, logarithmic changes are used to show the effect of changes in E_{tot}, and the logarithmic average of two elements in two periods is used to explore the effect of the contribution of factors. For additive decomposition, the changes in CO_2 emissions are decomposed using the following equation:

$$\Delta E_{tot} = \Delta E_Y + \Delta E_{\varphi_i} + \Delta E_{\theta_i}$$

$$= \sum_i L(e_i^t, e_i^{t-1}) \ln\left(\frac{Y^t}{Y^{t-1}}\right) + \sum_i L(e_i^t, e_i^{t-1}) \ln\left(\frac{\varphi_i^t}{\varphi_i^{t-1}}\right) + \sum_i L(e_i^t, e_i^{t-1}) \ln\left(\frac{\theta_i^t}{\theta_i^{t-1}}\right) \quad (3),$$

where the element, $L(e_i^t, e_i^{t-1})$, is given by the following:

$$L_i\ (e_i^t, e_i^{t-1}) = \frac{e_i^t - e_i^{t-1}}{\ln e_i^t - \ln e_i^{t-1}} \quad (4).$$

Combining equations (3) and (4), the three effects are calculated through the equations in the additive LMDI method as follows:

$$\Delta E_Y = \sum_i \frac{e_i^t - e_i^{t-1}}{\ln e_i^t - \ln e_i^{t-1}} \ln\left(\frac{Y^t}{Y^{t-1}}\right) \quad (5).$$

$$\Delta E_{\varphi_i} = \sum_i \frac{e_i^t - e_i^{t-1}}{\ln e_i^t - \ln e_i^{t-1}} \ln\left(\frac{\varphi_i^t}{\varphi_i^{t-1}}\right) \quad (6).$$

$$\Delta E_{\theta_i} = \sum_i \frac{e_i^t - e_i^{t-1}}{\ln e_i^t - \ln e_i^{t-1}} \ln\left(\frac{\theta_i^t}{\theta_i^{t-1}}\right) \quad (7).$$

2.2 Data and aggregation of sectors

This study utilizes the emission of pollutants for each sector between 1990 to 2015 from Nansai et al. (2009) and Nansai and Moriguchi (2012), known as 3EID, and the sectoral data provided by the Japan's domestic input-output table from 1980 to 2015. The 3EID provides information on energy consumption and emission factors for more than 30 types of fossil fuels, such as coke, fuel oil A, gasoline, and naphtha[2], which are directly consumed by sectors classified in the Japanese input-output table.

The reason for utilizing 3EID is that the calculation method of CO_2 emissions by using the information of consumption and emission factors of each type of energy source is consistent for all periods, which allows us to analyze the trend of CO_2 emissions.

When a new important industry in the Japanese economy emerges, a new sector will be defined within the input-output table. On the other hand, a sector will be aggregated into other sectors when the importance of the sector decreases. Hence, the number of sectors and the classification of sectors differs in each input-output table. To

[2] The waste matter-based energy sources are not considered in the calculation of CO_2 emissions.

overcome this issue, we reaggregate the original data consisting of more than 400 industries into 197 sectors so that the sector classification is consistent for the entire period.

We calculate the direct CO_2 emissions for 197 sectors based on CO_2 emission calculated in the 3EID. It should be noted that as the service sector consumes electricity and heat but does not consume fossil fuels directly. We estimate indirect CO_2 emissions from each sector based on the consumption of electricity, private power generation, and steam and hot water supply provided in the Value and Quantity Tables (VQT). [3]

We also calculated the weighted average of the market concentration ratio (top four firms) of relative sectors that corresponds to the sector classification by adopting information from the Japan Industrial Productivity (JIP) database[4].

3 Results and discussion

3.1 Change trends of total CO_2 emissions

This study attempts to analyze the changes in total CO_2 emissions at the national level. Concurrently, this study makes a modest attempt to analyze the changing trends and

[3] See Appendix A for the detailed method used to calculate the indirect emissions for each sector.

[4] The website of the database is https://www.ier.hit-u.ac.jp/English/databases/jip.html.

characteristics in Japan.

Figure 1 presents direct and indirect CO_2 emissions at the industrial level, highlighting the manufacturing, service, electricity, gas and heating supply industries. From 1980 to 2015 the Japanese industry experienced an increase in overall CO_2 emissions from 737 mt-CO_2 to 1,016 mt-CO_2, with the peak at 2015 (approximately 13% higher than that of the 1990 level). The decline in total CO_2 emissions during the period from 2005 to 2011 reflects the Great Financial Crisis from 2007 to 2008 and the Great East Japan Earthquake in 2011. For instance, we can observe that the total CO_2 emissions of the manufacturing industry gradually increased from 424 mt-CO_2 in 1980 to 477 mt-CO_2 in 2015. In 2015, while the CO_2 emissions of the manufacturing industry dropped by 4.2% compared to 2011, they still accounted for 47% of total CO_2 emissions. As evident from Figure 1, direct CO_2 emissions decreased while indirect emissions increased in the manufacturing industry. More importantly, the share of indirect emissions to total emissions increased during the study period, especially in the service industry, indicating that the structure of energy consumption within Japanese industries has gradually shifted away from fuel consumption towards electricity.

<Figure 1 approximately here>

Since the structure of energy consumption has shifted to electricity, indirect CO_2

emissions needs to be considered. Our analysis reveals that ignoring indirect emissions leads to the illusion that CO_2 emissions have decreased within the manufacturing industry since 1990. However, CO_2 emissions in the manufacturing industry have actually continued to increase since 2005, when indirect CO_2 emissions are considered. This implies that excluding indirect emissions can be misleading.

In contrast to the manufacturing industry, we find that the total CO_2 emissions of the service industry have increased significantly since 1980. It must be noted that the service industry does not use fossil fuels as much as the manufacturing industry. Thus, direct CO_2 emissions alone does not represent the actual situation of overall CO_2 emissions. Hence, indirect CO_2 emissions is very important. The indirect CO_2 emissions of the service industry grew by 53% from 1990 to 2015, from 43 mt-CO_2 to 67 mt-CO_2.

By comparing the share of total CO_2 emissions of the manufacturing and the service industry, we find that the share of the manufacturing industry declined from 58% to 48% whereas the percentage of the service industry doubled from 5.2% to 10.7% during the same period. This illustrates 1) the increase in economic activity of the service industry and 2) compared with manufacturing industry that successfully reduced CO_2 emissions, it seems that the CO_2 emissions from service industry has not been controlled well. To analyze the driving forces behind the changes in CO_2 emissions, we discuss the results of the additive LMDI method based on equation (4) in the next section.

3.2 Decomposition results at the industrial level

Figure 2(A) and 2(B) shows the industrial level results of the composition and the technique effect for the manufacturing and service industry, respectively. Since the scale effect represents the entire effect of all industries, it is not decomposed at the industrial level. The bar on the far right shows the overall effect between 1990 and 2011, when the VAP was implemented. For the manufacturing industry, during 1990 and 2011, the technique effect increased emissions by approximately 50 mt-CO_2 between 1990 and 2011, while the composition effect decreased emissions by more than 250 mt-CO_2 during the same period. The technique effect initially increased CO_2 emissions before 2000 and then reduced CO_2 emissions afterward, which achieved the maximum value between 1990 and 1995. This finding indicates that the CO_2 intensity has gradually improved compared with the prior period. The contribution of the composition effect in reducing emissions from the manufacturing industry reached 250 mt-CO_2 from 1990 to 2011, which may reflect the decline in domestic output and the fact that developing countries attracts dirty production processes or investments from developed countries due to lack of stringent environmental regulations (Copeland and Taylor, 2004).

<Figure 2 approximately here>

In contrast, Figure 2(B) shows a positive value for the composition effect for most periods, implying that the compositing the service industry increase CO_2 emissions. The technique effect from 1990 to 2011 is negative. However, if we look at the technique effect in detail, we observe that the technique effect is positive, meaning that it has increased CO_2 emissions since 2000. This finding indicates that the CO_2 emissions of the service industry cannot be ignored, and thus, it is necessary to consider regulations to reduce CO_2 emissions from the service industry.

3.3 Decomposition results for the sectors that participated in the VAP

The previous section focused on the entire manufacturing and service industry. However, the results for the sectors within the manufacturing industry may differ greatly due to the VAP. Thus, in this section we will focus on sectors that participated in the VAP, which not only provides the most detailed information on emission reduction but also allows us to investigate the effectiveness of the targets set forth under the VAP.

JFB announced the "Voluntary Action Plan on the Environment" in 1997. JFB's VAP allows industrial or trade associations to voluntarily set targets associated with CO_2 emissions, CO_2 intensity, energy consumption, and energy intensity, aiming to reduce the emissions from relevant firms by installing new environmental technology or improving the efficiency of their production processes. Note that none of the firms are obligated to achieve the target set by the associations within their sectors. Although the VAP is free from regulatory surveillance, the Japanese government conducts annual evaluation and verification of the progress made through relevant advisory councils.

<Table 2 approximately here>

Table 2 shows results of the composition and technique effect from 1990 to 2011 for sectors that participated in the VAP. These sectors are categorized into three groups by the type of target set by each sector. The first group is the absolute target, which specifies the total amount of GHG emissions or energy consumption reduction that must be achieved. The second group is the intensity target, which improves the emission intensity or energy intensity. The third group is the mixed target, which contains both absolute and intensity targets. Since emission reduction in the manufacturing sector in Japan mainly relied on the VAP before 2010, the technique effect between 1990 and 2011 can be partially reflected by the impacts of the VAP.

<Table 3 approximately here>

The composition effect is negative for approximately 70% of the sectors that participated in the VAP (Table 3). In contrast, the technique effect was negative for only 40% of the sectors. Compared with the decomposition results at the industrial level, the emission reduction for sectors that participated in the VAP is attributed to the composition effect, not the technique effect. Moreover, the relationship between the types of VAP targets and the signs of the technique effect is ambiguous. In particular, the technique effect for sectors with energy intensity targets do not exhibit negative values (i.e., a decrease in emission intensity), with the exception of the aluminum sector. This fact implies that the energy intensity target failed to reduce CO_2 emissions by improving production processes.

The decomposition results at the sector level did not show a clear-cut relationship between the type of target set under the VAP and the technique effect. To further explore why the impact of the VAP shows different signs for the technique effect at the sectoral level, we investigate the correlation between the technique effect and the market concentration (Figure 3). It is well-known that the market concentration[5] of a given sector is one of the most important characteristics that affects firm behavior. We find that sectors with markets that are more concentrated tend to have larger technique effects. This trend can be observed for the following reasons. Social pressure from investors and consumers has caused firms to become more socially responsible for their production and management. In addition, stakeholders have increasingly demanded that firms disclose information about their energy consumption and GHG emissions (Melville and Whisnant, 2014). Furthermore, the Japanese government conducts an annual evaluation and

[5] The market concentration becomes higher as the number of firms in the sector decreases, and vice versa.

verification of the progress in terms of how much each sector has fulfilled its VAP target. These evaluations and verifications are reported on the internet. The smaller the number of firms in a given sector, the social and association pressure placed on each firm is likely to increase (Azar et al., 2020). Hence, firms in a sector with higher market concentration are highly motivated to achieve the sectoral VAP target through the adoption of green production technologies, which is reflected in the technique effect. Therefore, the impact of the VAP is smaller for sectors with lower market concentration.

<Figure 3 approximately here>

We can consider another reason for this observation. In addition to large firms, SMEs that joined the JFB are also restricted under the VAP. However, the total R&D expenditure of large firms is 15 times higher than those of SMEs, based on a white study on SMEs in Japan, which indicates that large firms have more financial resources to carry out technological innovation than SMEs to meet the VAP target. Moreover, the sector with high market concentration is dominated by large firms. Thus, individual outcomes of efforts to reduce CO_2 emissions by large firms in a sector with high market concentration can appear more directly. In contrast, if a sector is constituted by many SMEs (a lower level of market concentration), the effect of emission reduction from VAP may be difficult to observe, since actions taken by small firms are not apparent compared to large firms. Thus, a positive sign of the technique effect is observed in Figure 3 for sectors with low market concentration.

4 Conclusions and policy implications

This study evaluated the effect of a VAP by adopting the additive LMDI method from 1980 to 2015 in Japan. Concurrently, this study also explored the driving forces behind CO_2 emissions at the disaggregated level in Japan and investigated the trend of direct and indirect CO_2 emissions. Our analysis revealed that the VAP might contribute to emission reduction among sectors where the number of competitors is limited. In other words, in an oligopolistic market, when firms are large in size and visible enough in the market, the VAP might give incentives to such firms to reduce CO_2 emissions or energy consumption. In such a case, firms face pressures from the society or the government to act environmentally or to adopt energy-efficient technologies.

The results of our analysis can be summarized as follows. National CO_2 emissions[6], excluding households, increased by 26% from 1980 to 2015. If we focus on indirect CO_2 emissions, it increased by 62% in the same period. This increase in the indirect emissions contributed to the increase in emissions from Japanese industries. Moreover, the structure of energy consumption, which has progressively shifted from

[6] In this study, we calculated the sectoral CO_2 emission in 1980 and 1985 using the CO_2 intensity of 1990.

fossil fuel to electricity in Japan, was explored in this study. Our decomposition result indicates that the emission reduction should be attributed to the composition effect, not the technique effect. Moreover, the decomposition results from the long-term analysis hint that the composition effect of the service industry led to the increase in CO_2 emissions. This result is due to the increase in the share of the service industry in the Japanese economy.

Evidence from our research suggests three directions for policy recommendations. First, we find that the VAP provides incentives to sectors with high market concentration to reduce CO_2 emissions. However, our analysis also suggests that the contributions of the VAP may be limited, as the VAP fails to reduce CO_2 emissions for sectors with low market concentration and sectors with energy-intensive targets. Even in an oligopolistic market, when the size of firms is small, the VAP may also fail to reduce emissions. Moreover, our results show that the energy intensity target failed to reduce CO_2 emissions, which indicates that energy efficiency was not improved though the VAP. To achieve carbon neutrality by 2050, VAP effort will certainly be insufficient. Furthermore, the allocation of resources across sectors is outside the scope of the VAP. Thus, a policy instrument that shifts resources between sectors may be needed. Economic instruments such as a carbon tax or national ETS are more appropriate policy instruments from these perspectives.

Second, this study also analyzes indirect CO_2 emissions from the electricity sector. The results show the increases in indirect CO_2 emissions in Japan, especially in the service industry. Therefore, it is crucial to implement low carbonization and decarbonization regulations targeting the service industry. The current Japanese regulation on the service sector focuses on energy efficiency and fails to provide incentives for decarbonization[7]. In other words, the carbon content must be reduced and decarbonized from electricity. For instance, the spread of renewable energy or a set of limits or standards for CO_2 emissions from electricity generating units in Japan's power sector would be effective[8]. Japan has already adopted feed-in tariffs and is now moving to feed-in premiums. These policies must be continued and expanded to offer an incentive for emission reduction from electric power companies. Moreover, to promote the procurement of renewable energy by private firms, the Ministry of the Environment of Japan encourages participation in RE100, which is a global initiative for enterprises committing to using 100% renewable electricity. This trend toward RE100 will be useful in improving the CO_2

---

[7] In Japan, the energy conservation act, which also targets the service industry, focuses on reducing energy consumption or improving energy efficiency (Arimura and Iwata, 2015). Therefore, the act does not give strong incentives for decarbonization.

[8] The government of California signed the Clean Energy and Pollution Reduction Act of 2015 to set the goal of generating half of the state's electricity from renewable sources by 2030 and doubling its energy efficiency (U.S. Environmental Protection Agency, 2016).

intensity of the power sectors. Moreover, Japan's service industry is not fully covered by the VAP. In the service industry, unlike in the manufacturing industry, it is probable that the power of industrial associations is weaker and, thus, that the VAP cannot be successfully implemented. Therefore, carbon pricing such as the Tokyo ETS, which targets the commercial sector and has succeeded in reducing emissions (Arimura and Abe, 2021), will be effective in the non-manufacturing industries.

Third, we observe that the technique effect has reduced CO_2 emissions in the manufacturing industry since 2000. However, in recent years, the range of the reduction from the technique effect has disappeared, which indicates the following. (1) The VAP shows limited improvement for abatement; thus, policies to promote innovations are necessary, and the government should implement policies that focus on providing incentives to invest in low-carbon technologies or adopt instruments such as carbon pricing. (2) Future improvement in the combustion efficiency of fossil fuels is unrealistic; in this case, it is necessary to promote electrification, the expansion of renewable energy, and technological innovation.

The VAP is a sectoral level effort by industry associations. Therefore, to investigate the impact of VAP at the detailed sectoral level, researchers can use input-output tables as an analytic tool. In this sense, we provide reasonable results in the sectoral level analysis of VAP. However, our results should be interpreted with caution for several reasons. First, we adopt a factor based on the VQT, which is supplementary information provide along with the domestic input-output table, of 1995 to recount the tables in the other years because the quantity of the business power and heat supply sector in the VQT suddenly decreased in 2000 and 2005, leading to the calculation of the outlier of indirect CO_2 emissions compared with the data from the Greenhouse Gas Inventory Office of Japan.

Second, this study did not analyze the impact of energy prices and the innovation from other factors within the technique effect, as we focused on the effect of VAP. Although the impact of energy price is not considered, the Japanese economy relies on fossil fuel imports from other countries; thus, the impact from fossil fuels on each sector will be similar. Therefore, the missing fossil fuel price influences the results of every sector uniformly, and hence, bias may be limited. The innovation resulting from factors other than VAP or energy prices cannot be observed through the input-output table, which is also a limitation in our analysis.

Finally, although we confirmed the drivers behind the changes in CO_2 emissions and proposed policy recommendations at the sectoral level, we may have oversimplified the results. For countries with a decentralized system, it might be challenging to introduce new regulations at the national level. In this case, regulations at the regional level may be more appropriate. If so, a regional analysis will be useful in designing regulation at the regional level. However, the limitations of the data restrict us from sectoral analysis at the regional level.

Furthermore, this study does not consider the technical change in the energy sector, which may lead to an overestimation of CO_2 emissions in recent years. How much did the technical innovation of the power and heat supply sector contribute in reducing indirect emissions? Are there co-benefits, such as SO_2, SPM, and NO_x reduction, by reducing CO_2 emissions? We leave these questions for the future.

Acknowledgements

We acknowledge with gratitude the helpful comments and suggestions from Professor Masahiro Sugiyama (Institute for Future Initiatives, University of Tokyo), Professor Yutaka Tonooka, and Professor Akira Sasahara (Faculty of Economics, Keio University). We are grateful for the helpful comments from the conference participants at the 25th Annual Conference of the Society for Environmental Economics and Policy Studies (2020), the 2020 Annual Conference of the Society of Environmental Science (2020), and the 4th Sophia Research Workshop in Economics (2021).

Funding

Toshi Arimura, Makoto Sugino and Guanyu Lu appreciate financial support from the Environment Research and Technology Development Fund (JPMEERF20202008) of the Environmental Restoration and Conservation Agency and the Sompo Environment Foundation. Toshi Arimura is grateful to the financial support from Waseda Institute for Political Economy.

Data availability

The data set used in the analysis is available upon request.

References

Ang, B.W., 2004. Decomposition analysis for policymaking in energy. Energy Policy 32, 1131–1139. https://doi.org/10.1016/s0301-4215(03)00076-4.

Ang, B.W., 2005. The LMDI approach to decomposition analysis: a practical guide. Energy Policy 33, 867–871. https://doi.org/10.1016/j.enpol.2003.10.010.

Ang, B.W., 2015. LMDI decomposition approach: a guide for implementation. Energy Policy 86, 233–238. https://doi.org/10.1016/j.enpol.2015.07.007.

Arimura, H.T., 2015. Japanese domestic environmental policy: with a focus on climate change and air pollution policy, in: Managi, S. (Ed.), The Routledge HandBook of Environmental Economics in Asia. Routledge, London, UK, pp. 516–553.

Arimura, T.H., Abe, T., 2021. The impact of the Tokyo emissions trading scheme on office buildings: what factor contributed to the emission reduction? Environ. Econ. Policy Stud. https://doi.org/10.1007/s10018-020-00271-w.

Arimura T.H., Iwata, K., 2015. An Evaluation of Japanese Environmental Regulations: Quantitative Approaches from Environmental Economics. Springer, pp. 191

Arimura, T.H., Kaneko, S., Managi, S., Shinkuma, T., Yamamoto, M., Yoshida, Y., 2019. Political economy of voluntary approaches: a lesson from environmental policies in Japan. Econ. Anal. Policy 64, 41–53. https://doi.org/10.1016/j.eap.2019.07.003.

Azar, J., Marinescu, I., Marshall, S., 2020. Labor market concentration. J. Hum. Resour. 55. https://doi.org/10.3368/jhr.monopsony.1218-9914R1.

Cansino, J.M., Román, R., Ordóñez, M., 2016. Main drivers of changes in CO_2 emissions in the Spanish economy: a structural decomposition analysis. Energy Policy 89, 150–159. https://doi.org/10.1016/j.enpol.2015.11.020.

Copeland, B, R., Taylor, M., 2004. Trade, Growth, and the Environment. Journal of Economic Literature 42, 7-71. https://doi.org/10.1257/002205104773558047.

Grossman, G, M., 1995. Pollution and growth: What do we know?. I Goldin, L.A Winters (Eds.), The Economics of Sustainable Development, Cambridge University Press, Cambridge (1995), pp. 19-47

Jones, R., Yoo, B., 2009. Improving the Policy Framework in Japan to Address Climate Change. OECD Economics Department Working Studys, No. 740. OECD Publishing, Paris.

Levinson, A., 2009. Technology, International trade, and pollution from US manufacturing. Am. Econ. Rev. 99, 2177–2192. https://doi.org/10.1257/aer.99.5.2177.

Lin, B., Lei, X., 2015. Carbon emissions reduction in China's food industry. Energy Policy 86, 483–492. https://doi.org/10.1016/j.enpol.2015.07.030.

Liu, N., Ma, Z., Kang, J., Su, B., 2019. A multi-region multi-sector decomposition and attribution analysis of aggregate carbon intensity in China from 2000 to 2015. Energy Policy 129, 410–421. https://doi.org/10.1016/j.enpol.2019.02.015.

Matsumoto, K., Shigetomi, Y., Shiraki, H., Ochi, Y., Ogawa, Y., Ehara, T., 2019.

Addressing key drivers of regional CO_2 emissions of the manufacturing industry in Japan. Energy J. 40, 233–258. https://doi.org/10.5547/01956574.40.si1.kmat.

Melville, N.P., Whisnant, R., 2014. Energy and carbon management systems. J. Ind. Ecol. 18, 920–930. https://doi.org/10.1111/jiec.12135.

Nansai, K., Kagawa, S., Suh, S., Fujii, M., Inaba, R., Hashimoto, S., 2009. Material and energy dependence of services and its implications for climate change. Environ. Sci. Technol. 43, 4241–4246. https://doi.org/10.1021/es8025775.

Nansai, K., Moriguchi, Y., 2012. Embodied Energy and Emission Intensity Data for Japan Using Input – Output Tables (3EID): For 2005 IO Table CGER, National Institute for Environmental Studies, Japan, www.cger.nies.go.jp/publications/report/d031/index.html.

Nishitani, K., Kaneko, S., Fujii, H., Komatsu, S., 2012. Are firms' voluntary environmental management activities beneficial for the environment and business? An empirical study focusing on Japanese manufacturing firms. J. Environ. Manag. 105, 121–130. https://doi.org/10.1016/j.jenvman.2012.03.054.

Okamoto, S., 2013. Impacts of growth of a service economy on CO_2 emissions: Japan's case. J. Econ. Struct. 2, 8. https://doi.org/10.1186/2193-2409-2-8.

Shigetomi, Y., Matsumoto, K.I., Ogawa, Y., Shiraki, H., Yamamoto, Y., Ochi, Y., Ehara, T., 2018. Driving forces underlying sub-national carbon dioxide emissions within the household sector and implications for the Paris agreement targets in Japan.

Appl. Energy 228, 2321–2332. https://doi.org/10.1016/j.apenergy.2018.07.057.

Su, B., Ang, B.W., Li, Y., 2017. Input-output and structural decomposition analysis of Singapore's carbon emissions. Energy Policy 105, 484–492. https://doi.org/10.1016/j.enpol.2017.03.027.

Sugino, M., Arimura, T.H., 2011. The effects of voluntary action plans on energy-saving investment: an empirical study of the Japanese manufacturing sector. Environ. Econ. Policy Stud. 13, 237–257. https://doi.org/10.1007/s10018-011-0015-1.

Sugiyama, R., Imura, H., 1999. Voluntary approaches in Japan: proven record of pollution control agreements and new industrial initiatives for the protection of the global environment. Eco-Manag. Audit. 6, 128–134. https://doi.org/10.1002/(sici)1099-0925(199909)6:3<128::aid-ema104>3.0.co;2-a.

U.S. Environmental Protection Agency, 2016. Cutting power sector carbon pollution: state policies and programs. https://www.epa.gov/ (accessed 10 September 2020).

United Nations Framework Convention on Climate Change, 1997. Kyoto protocol. http://www.unfccc.de (accessed 10 September 2020).

Wakabayashi, M., Arimura, T.H., 2016. Voluntary agreements to encourage proactive firm action against climate change: an empirical study of industry associations' voluntary action plans in Japan. J. Clean. Prod. 112, 2885–2895. https://doi.org/10.1016/j.jclepro.2015.10.071.

Wang, M., Feng, C., 2017. Decomposition of energy-related CO_2 emissions in China: an empirical analysis based on provincial panel data of three sectors. Appl. Energy 190, 772–787. https://doi.org/10.1016/j.apenergy.2017.01.007.

Wang, Z., Jiang, Q., Dong, K., Mubarik, M.S., Dong, X., 2020. Decomposition of the US CO_2 emissions and its mitigation potential: an aggregate and sectoral analysis. Energy Policy 147, 111925. https://doi.org/10.1016/j.enpol.2020.111925.

Xie, X., Lin, B., 2019. Understanding the energy intensity change in China's food industry: a comprehensive decomposition method. Energy Policy 129, 53–68. https://doi.org/10.1016/j.enpol.2019.02.003.

Zhang, W., Li, K., Zhou, D., Zhang, W., Gao, H., 2016. Decomposition of intensity of energy-related CO_2 emission in Chinese provinces using the LMDI method. Energy Policy 92, 369–381. https://doi.org/10.1016/j.enpol.2016.02.026.

Zhang, W, C., Pend, S, J., Sun, C, W., 2015. CO_2 emissions in the global supply chains of services:Ananalysis based onamulti-regionalinput–output model. Energy Policy 86, 93–103. https://doi.org/10.1016/j.enpol.2015.06.029.

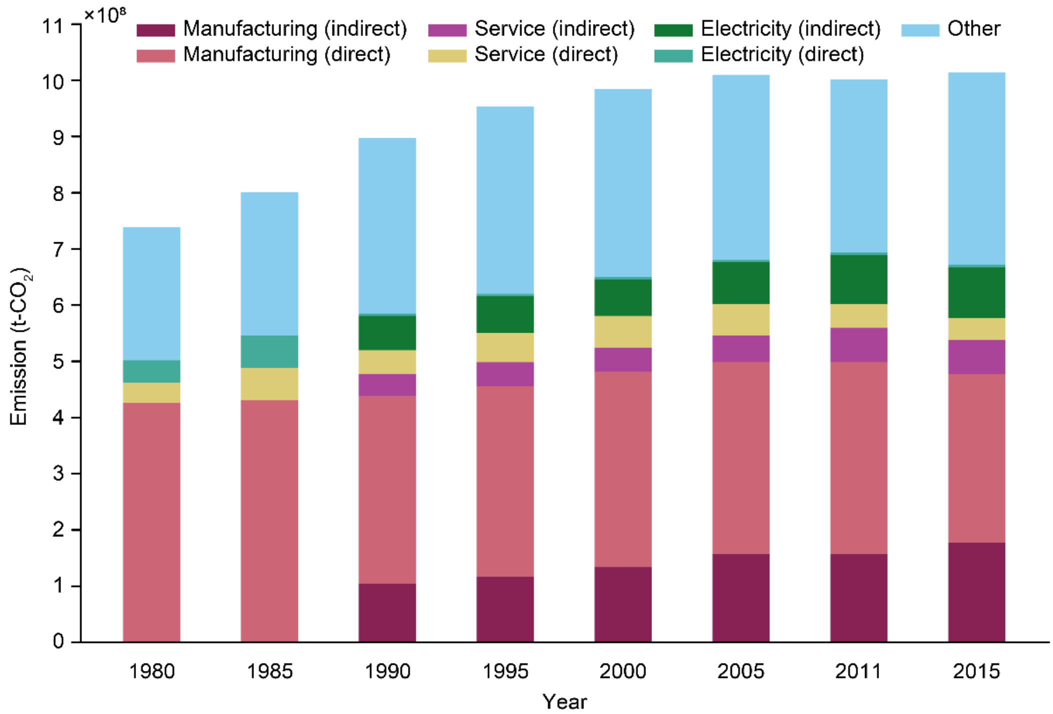

Figure 1. Direct and indirect CO_2 emissions at the industrial level

Note: We use 1990 emission intensities to calculate sectoral CO2 emissions for 1980 and 1985. Thus, the CO2 emissions from 1980 to 1985 are not decomposed into direct or indirect emissions. The light color represents direct CO2 emissions.

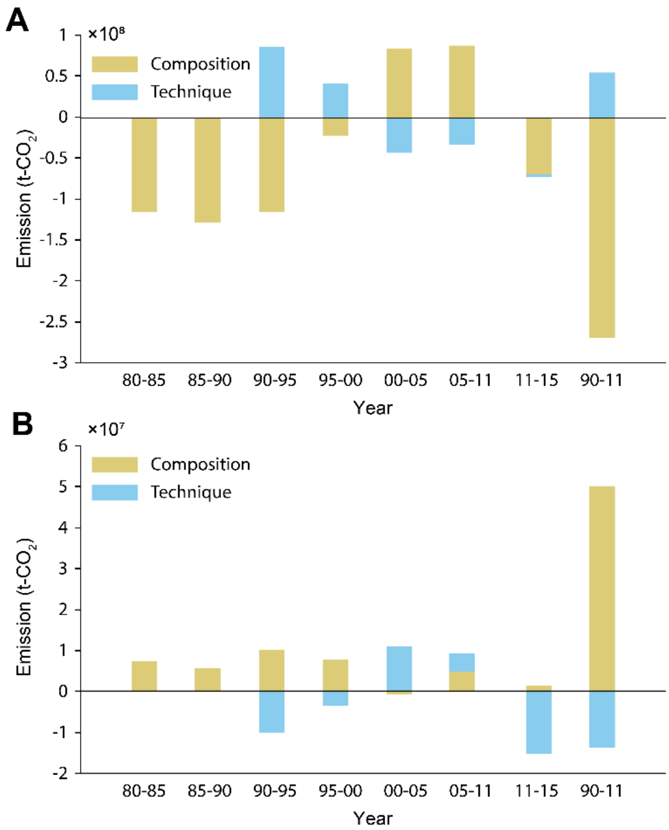

Figure 2. Composition and technique effects for the manufacturing and service industry

Note: "80–85" in the figure indicates the period from 1980 to 1985.

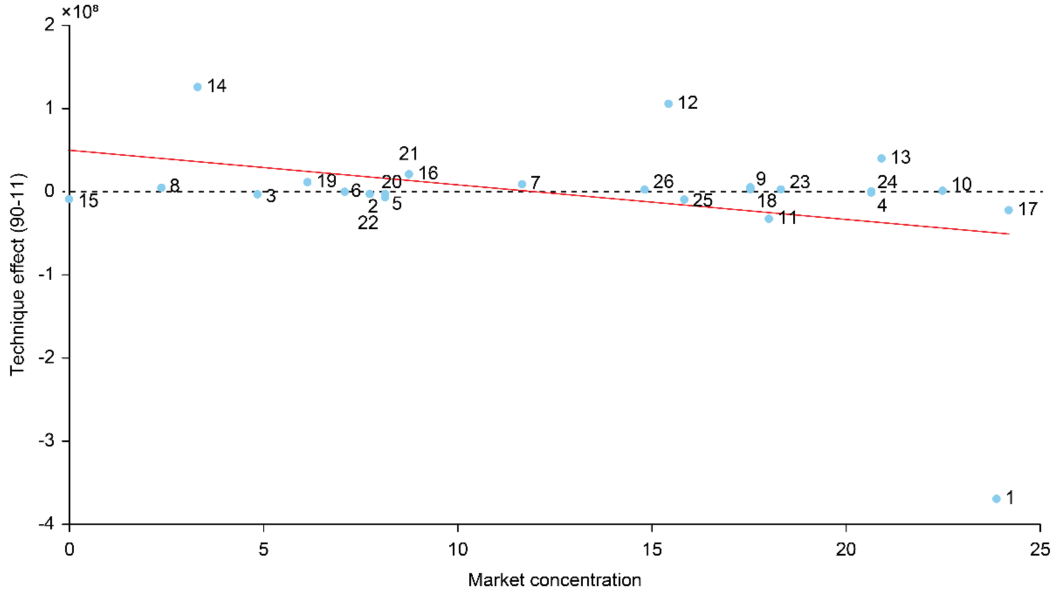

Figure 3. Relationship between the technique effect and market concentration

Note: The numbers in this figure correspond to the numbers in Table 2. The R-square value and t statistic are 0.12 and 1.84, respectively.

Table 1. Summary of the existing literature

Publication	Time Period	Target sector	Number of sectors or industries	Research technique	Indirect CO_2
Japan					
Matsumoto et al. (2019)	1993 to 2013	Japan's manufacturing Industry	8	Additive LMDI	N
Okamoto (2013)	1990 to 2005	Japan's primary, secondary industry and other 2 industries	4	Shapley–Sun decomposition method	N
Shigetomi et al. (2018)	1990 to 2015	Japan's household sector	1	Multiplicative LMDI	N
Other countries					
Xie and Lin (2019)	2000 to 2013	China's food industry	1	Multiplicative LMDI	N
Wang et al. (2020)	1997 to 2016	US's residential, commercial, and other 2 sectors	4	Additive LMDI	Y
Liu et al. (2019)	2000 to 2015	China's agriculture, mining, and other 14 sectors	16	Multiplicative LMDI	N
Cansino et al. (2016)	1995 to 2011	Spain's agriculture, mining, and other 33 sectors	35	Additive LMDI	N
Su et al. (2017)	2000 to 2010	Singapore's agriculture, manufacturing, and other 8 industries	110	Structural decomposition analysis	Y
Lin and Lei (2015)	1986 to 2010	China's food industry	1	Additive LMDI	Y

Table 2. Sectors that participated in the VAP.

Sector name	Code
Sectors with an absolute target	
Pig iron	1
Industrial equipment	2
Sugar	3
Railway	4
Sake (liquors)	5
Sanitary equipment (medical instruments)	6
Pharmaceuticals (medicaments)	7
Residential	8
Electric wire	9
Glass	10
Sectors with an intensity target	
Petroleum product	11
Chemical-related sectors	12
Paper	13
Cement	14
Construction	15
Mining (gravel, quarrying)	16
Aluminum	17
Copper	18
Bearing	19
Beverage	20
Limestone	21
Machine tool	22
Milling	23
Ship	24
Sectors with a mixed target or other target	
Production of car bodies and parts	25
Rubber	26

Note: The translation of the sectors in this table is based on the report of VAP.

Table 3. Effects from 1990 to 2011

Sector name	Effects (10^5 t-CO_2) Composition	Technique
Sectors with an absolute target		
Pig iron	-768.01	-369.603
Industrial equipment	10.34	-2.199
Sugar	-13.76	-3.324
Railway	0.16	-0.207
Sake (liquors)	-0.36	-6.146
Sanitary equipment (medical instruments)	1.55	0.01
Pharmaceuticals (medicaments)	1.57	9.34
Residential	-10.03	4.83
Electric wire	-5.42	5.08
Glass	-28.95	1.60
Sectors with an intensity target		
Petroleum product	-218.01	-32.88
Chemical-related sectors	-107.57	106.75
Paper	-76.25	39.82
Cement	-296.11	126.67
Construction	3.47	-8.27
Mining (gravel, quarrying)	-29.82	21.39
Aluminum	-8.80	-22.33
Copper	-3.64	2.67
Bearing	-10.01	12.65
Beverage	38.21	-2.49
Limestone	-29.82	21.39
Machine tool	10.34	-2.19
Milling	-3.14	2.54
Ship	-2.62	0.65
Sectors with a mixed target or other target		
Production of car bodies and parts	20.58	-8.68
Rubber	-13.04	2.14

A. Appendix

A.1 Calculation of indirect CO_2 emissions

Indirect CO_2 emissions is defined as CO_2 emissions emitted from power generation and heat. First, we calculate the emission intensity for electricity, private power generation and steam and hot water supply for all periods t, using the following equation:

$$Emission\ intensity_j^t = \frac{CO_2\ emissions_j^t}{TC_j^t} \quad \text{(A.1)},$$

where j represents electricity, private power generation, and steam and hot water supply, t represents 1980, 1985, 1990, 1995, 2000, 2005, 2011, and 2015, and TC_j^t represents the total consumption of energy j at time t. Next, using the emission intensity calculated above, we can calculate indirect CO_2 emissions for sector i at time t as:

$$Indirect\ CO_2\ emissions_{ij}^t = Emission\ intensity_j^t \times EC_{ij}^t \quad \text{(A.2)},$$

where EC_{ij}^t is the consumption of electricity, private power generation, or steam and hot water supply for each sector i at time t.

In theory, we can calculate indirect emissions for each industry using equation (A.2). However, there is a critical issue that needs to be addressed concerning the VQT. The volume of energy consumption for a few sectors fluctuates from the previous year, which leads to drastic increases and decreases in the value of indirect CO_2 emissions.[9]

---

[9] The indirect emissions calculated from the data reported in the VQT differs from the

Therefore, we apply the share of consumption reported in the VQT for 1995 to estimate the amount of energy used for 1990, 2000, 2005, 2011 and 2015. This means that we ignore improvements in energy consumption achieved by each sector i.

We estimate the amount of energy used for 1990, 2000, 2005, 2011 and 2015 using the following equations for electricity, private power generation, and steam and hot water supply

$$Input\ ratio_{ij}^{1995} = \frac{Energy\ Consumption_{ij}^{1995}}{\sum_{i}^{197} Energy\ Consumption_{ij}^{1995}} \qquad \text{(A.3)},$$

$$\widehat{EC_{ij}^{t}} = Input\ ratio_{ij}^{1995} \times \sum_{i}^{197} Energy\ Consumption_{ij}^{t} \qquad \text{(A.4)}.$$

where the total consumption of energy j is the sum of consumption of energy j at all sectors. Finally, we calculate indirect emissions for each sector by replacing EC_{ij}^{t} with $\widehat{EC_{ij}^{t}}$ in equation (A.2).

---

national inventory data provided by National Institute for Environmental Studies of Japan, https://www.nies.go.jp/gio/aboutghg/index.html.